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Abstract

This paper reports on an empirical investigation into the ability of Artificial Neural Network (ANN) technique in learning and predicting preference. ANNs were used to learn preference patterns of holistic judgments on a sample of multi-criteria decision alternatives defined by the orthogonal design. Then a comparative study was conducted with utility theory-based models and ANNs to predict decision makers' choice. In all cases, the predictive ability of ANN was found to be as good as or better than those of utility theory-based models.

Introduction

Multi-criteria decision making (MCDM) involves making choices on a set of alternatives, taking into consideration many conflicting qualitative and/or quantitative criteria. To determine a preference profile, literature has suggested various assessment techniques based on the utility theory. Thus far, however, the agreement among decision maker (DM)'s preferences assessed by using different methods has been inconclusive. Assuming that the DM is rational, the incompatibility of reported results may stem from the prescribed form of the utility function being used. To address the possible problem with models which inadequately represent the incomplete knowledge on a DM's decision patterns, in particular by using an inappropriate utility function, we consider the use of Artificial Neural Network (ANN). The technique is well suited for detecting associations among patterns in environments that are characterized by partial information.

Modeling Preference with Utility Theory

Given that one accepts the axioms of utility theory (Von Neumann and Morgenstern, 1944), the expected utility criterion can be used to identify the best alternative in making a choice. The most commonly used utility function is Keeney's multi-attribute utility (MAUT) function (Keeney, 1974; Keeney & Raiffa, 1976). Keeney states that, for the number of attributes (criteria) $n \geq 3$, the MAUT function can be prescribed either in an additive form,

$$u(x) = \sum_{i=1}^{n} k_i u_i(x_i) \qquad (1)$$

or in a multiplicative form

$$1 + ku(x) = \prod_{i=1}^{n} [1 + kk_i u_i(x_i)] \quad (2)$$

where u, u_i are utility functions scaled from zero to one; k_i, $0 < k_i < 1$, is the weight of single attribute utility function u_i; $k > -1$ is a non-zero constant and is the solution to

$$1 + k = \prod_{i=1}^{n} [1 + kk_i] \qquad (3)$$

The parameters of MAUT function are assessed with either a decomposition method or a holistic method. In the decomposition approach, the preference for each possible level of a criterion is assessed with reference to utilities for the best and worst levels. Then single attribute utility functions are aggregated in the prescribed form to represent the preference for an MCDM problem. In the holistic approach, the overall preference for an alternative is assessed with reference to utilities for the best and worst alternatives in the problem domain. Then the traditional regression, the Analysis of Variance or a nonlinear optimization technique is used to estimate the function parameters. In both approaches, one can use the estimated utility function to generalize over future instances.

So far, comparative studies have not always shown a strong agreement between decomposition and holistic assessments of DM's preference. One possible explanation may be the DMs were not consistent and had difficulties in expressing their preferences. However, Slovic and Lichtenstein (1971) found that people can and do assign values to multi-attribute outcomes in a consistent and meaningful manner. Another reason could be the inappropriately prescribed utility function. In fact, Einhorn and Hogarth (1981) argued that there is no theory or set of principles that would resolve the appropriateness of intuitive responses and optimal models in decision making. In view of these somewhat inconsistent empirical findings and controversial theory developments, perhaps the DM's preference profile may not been captured entirely by Keeney's MAUT function. The mapping of behavioral aspect of the DM's preference would require a more flexible functional form than the one prescribed by the utility theory, the structure of which would permit less precision when the precision is not necessary. This is exactly the strength of an ANN in its ability to recognize functional forms which are more general than the linear superpositions and orthogonal functions of classical statistical methods.

Learning and Predicting Preference with Artificial Neural Networks

An ANN can be considered as a universal approximator of any functional relationship. The Kolgomorov theorem establishes a perfect mapping from R^n to R^m as long as an appropriate transfer function is chosen. It has been shown that a standard multi-layer network with any arbitrary transfer function can approximate any continuous or discontinuous function to any degree of accuracy without imposing any nonsample restriction on the observations (Cybenko, 1989; Hornik et al., 1989). In an MCDM context, an ANN can learn and predict a DM's preference without specifying his/her utility function, *a priori*. With enough data and an appropriate topology, an ANN would generate a better representation of decision patterns than the utility theory-based assessment procedure.

This study investigates the ability of the ANN technique in predicting a DM's preference after learning his/her decision patterns from a sample of holistic preferences. Hidden behind the holistic assessment of alternatives in a problem domain, there always exits a logical reason on the association between input (criteria) and output (decision) patterns. The use of holistic assessment intends to alleviate the difficulty of DM in expressing explicitly the trade-offs among criteria of the decision problem. In addition, an orthogonal plan (Addelman, 1962) is designed to provide an optimal sample of alternatives for holistic assessment in order to reduce the information processing burden on DM. Given the existence of an underlying utility function, the ANN technique is able to learn from decision patterns and then predict preference without imposing strong assumptions on decision behavior and functional form of preference.

The decision problem in this study relates to the project evaluation and economic appraisal of proposals for new products in a manufacturing company. These proposals are evaluated on five criteria. The problem domain is presented in Table 1. Some criteria are quantitative, others are qualitative. In the appraisal process, the quantitative data are arbitrarily converted into categories to avoid the difficulty in dealing with data on a continuous scale. An orthogonal plan is used to define an optimal sample of 24 examples taken from all possible alternatives in the problem domain. As an illustration, in ANN learning the pattern of the alternative "A proposal has an NPV of cash flow of 1 million, requires an initial investment of 2 millions; the proposed product has a good market growth rate, a very good capability to market and a very good prospect of technical success" is coded as [1 2 2 3 3] . The performance of the assessment method is tested on five out-of-sample alternatives. For each alternative in the training set and test set, the DM will provide his/her holistic preference. ANN will learn the preference patterns from the training set and generalize over the out-of-sample test set.

Table 1. Problem Domain

NPV of Cash Flow	$[1.0	2.0	3.0	4.0	5.0] millions
Initial Investment	$[2.5	2.0	1.5	1.0	0.5] millions
Market Growth Rate		[fair	good	very-good]	
Capability to Market		[fair	good	very-good]	
Prospect of Technical Success		[fair	good	very-good]	

The preference profiles were assessed from nine graduate students enrolled in a business school in Montreal. MAUT functions were assessed with procedure described in Keeney (1977). Applying the ANN technique, a 3-layer network configuration using a backpropagation algorithm was implemented in which the input layer had six nodes, each representing a decision criterion, and the output layer had one node representing the approximated utility. In order to capture the complexity of the underlying utility function, the number of nodes in the hidden layer varied from four to six. Thus the ANNs in study have configurations of 6-4-1, 6-5-1 and 6-6-1 which are indicated as ANN4, ANN5 and ANN6, respectively.

Preliminary Results

The relative performance in predicting preference on out-of-sample alternatives is evaluated across assessment methods and subjects. Using holistic judgment to represent the DM's intuitive preference as the benchmark, the performance of each method is measured by the Kendall rank correlation between the result obtained from the related method and the holistic one. Between the ranks obtained from MAUT method and holistic assessment, the range of Kendall rank correlation is from -.32 to .95 with a median of .40. Between ANN4 and holistic assessment, the range is from .32 to 1.00 with a median of .84. Between ANN5 and holistic assessment, the range is from -.11 to 1.00 with a median of .74. Between ANN6 and holistic assessment, the range is from .11 to .84 with a median of .74.

Out of nine subjects in the study, between MAUT method and holistic assessment, the same best project was identified in 5 cases, the same worst was identified in 4 cases. Between ANN4 and holistic assessment, the same best project was identified in 7 cases, the same worst was identified in 5 cases. Between ANN5 and holistic assessment, the same best project was identified in 5 cases, the same worst was identified in 6 cases. Between ANN6 and holistic assessment, the same best project was identified in 5 cases, the same worst was identified in 4 cases.

Concluding Remarks

The results reported in this study have demonstrated the ability of ANN in learning decision patterns and predicting decisions that closely represent intuitive preference. Overall, in any configurations, the performance of ANN in predicting preference is at least as good as the one of utility-theory based method. The approximation of utility function by ANN is based on a rigorous theory of function mapping. It does not impose any strong assumption on decision behavior in order to fit human preference in a prescribed functional relationship. This finding should be useful in building effective expert systems and decision support systems. In particular, ANN should become an alternative to the traditional knowledge engineering technology which cannot function with partial information on DM's preference, i.e., incomplete rule set. Elsewhere, we have proposed to use the preference captured in an optimal training set as the initial knowledge base for an integration of ANNs and expert systems.

In a future work, we shall address the modeling of DM's imprecise judgments with fuzzy logic. An ANN integrated with fuzzy logic will learn human preference better and provide more accurate prediction. In another work, we shall extend the scope of machine learning with ANN from individual preference to group preference.

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